The Causal Effect of High Occupancy Vehicle Lanes on Commuting Times in California

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Abstract

The effects of high occupancy vehicle (HOV) lanes studied from a causal perspective have been minimal in the economics literature. Knowing the impacts of these types of infrastructure projects is beneficial in terms of public policy and resource allocation. Using an instrumental variable (IV) approach to overcome the endogeneity problems associated with HOV lane location selection, this study aims to uncover the impacts of HOV lanes on commuters' time spent going to and coming home from work in California. Making use of the 2017 National Household Travel Survey, and after data pre-processing through coarsened exact matching (CEM), this paper finds that both having HOV lanes in workplace counties and living closer to HOV lanes cause increased commute times to and from work for commuters, lending credence to earlier works on road construction and traffic outcomes citing induced demand from increased road construction (Duranton & Turner, 2011).

Keywords: HOV lanes, congestion policy, commute times, National Household Travel Survey

JEL Classification: R0, R42, H40

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From correlational psychological surveys to more causal empirical econometric techniques, extensive work has been conducted to uncover the effects of the negative externalities associated with traffic congestion. The policy response to combat congestion has varied across urban areas throughout the world. Several places have implemented congestion pricing in city-centers or high traffic areas to decrease the marginal benefit of traveling in the tolled area during peak travel times. Several well-known examples include London (Leape, 2006), Stockholm (Eliasson, 2009), and the country of Singapore (Santos, 2005). New York City recently became the first U.S. city to embrace congestion pricing to help curb congestion.[1]

One of the many proposed solutions to help eliminate traffic congestion, specifically congestion associated with commuting, are high occupancy vehicle (HOV) lanes. Each vehicle that wishes to travel in an HOV lane must be carrying the minimum number of people posted at the entrance sign. A notable characteristic of an HOV lane is that there is no charge associated with its use.[2]

In many urban centers across the United States, policy makers and urban planners tout the advantages of the construction of HOV lanes; some of the benefits cited include improving highway efficiency in terms of congestion, vehicle volumes, and emissions. In addition, many state and federal reports cite the benefits of HOV lanes over general purpose lanes and exempt these lanes from certain regulations that general purpose road lanes face.[3] Despite the rising costs of road construction and repair, minimal efforts have been conducted to determine whether or not HOV lanes have been effective in reducing driving times or congestion. For example, in 2012, just 10 miles of HOV lane construction in Los Angeles county cost over $10 billion. Understanding the mechanisms behind these special road lane policies would be beneficial to both urban planners and commuters alike.

To attempt to analyze the effects of HOV lanes on traffic congestion, I employ an instrumental variable technique to capture the causal effects of HOV lanes on commuting times in California. After data pre-processing using coarsened exact matching (CEM), the vote share for Al Gore in the 2000 presidential election is used to instrument for the location of HOV lanes in California,

[1] Source: https://www.nytimes.com/2019/03/31/nyregion/budget-new-york-congestion-pricing.html

[2] This is in contrast with high occupancy toll (HOT) lanes, where a toll is also required in addition to the carpooling guidelines.

[3] http://www.dot.ca.gov/trafficops/tm/hov.html outlines the California laws governing the purpose of HOV lanes.

as well as the distance commuters live from the nearest HOV lane. As additional robustness, the 1947 highway plan used in Baum-Snow (2007), Duranton and Turner (2011), and others is used to instrument for the location of HOV lanes in California, as well as the distance commuters live from the nearest HOV lane. This paper finds evidence that additional HOV lanes in commuters' workplace counties and living near HOV lanes lead to higher commute times to and from work and thus are not meeting the goals of policymakers. Arguably, the induced demand to drive on a route from the construction of an HOV lane increases the commute time of *all* commuters who take that route, not just the ones who take the HOV lane. This finding extends the results found in previous studies on induced demand for roadway usage by showing these results hold true even for heterogeneous road lane types.

The remainder of the paper is as follows: Section 1 discusses publications surrounding HOV lanes and commuting and highlights the major trends in the literature; Section 2 details the data sources used; Section 3 outlines methods and model specifications used to identify the causal relationship between HOV lanes and commuting times in California; results and robustness checks are discussed in Section 4, along with limitations of the current study design; Section 5 concludes.

I Literature: Commuting and HOV Lanes

There is a large literature base that examines the impacts of traffic congestion in general. Several psychology studies, including Hennessy and Wiesenthal (1999) note the adverse effects associated with sitting in traffic congestion. Specifically, increased time spent in traffic congestion is associated with increased aggressiveness. Following in this vein, the majority of the work on traffic congestion in economics has focused on the health outcomes of those directly impacted by the congestion.[4] Currie and Walker (2011) examine the impact of pollution from E-ZPass terminals[5] along interstates. This study finds that mothers who lived closer to these terminals necessarily live along highways prone to more traffic congestion, hence more pollution in the air; these women gave birth to children with significantly lower birth weights when compared to mothers living

[4]There have also been several studies that try to quantify quality of life indexes taking congestion levels into account. See Albouy and Lue (2015) for example.

[5]E-ZPass is an electronic toll collection system used on most tolled roads, bridges, and tunnels in the Midwestern and Eastern United States. These electronic toll collection terminals can become quite congested during peak rush hour times.

near, but not as close to the E-ZPass terminals. Knittel, Miller, and Sanders (2016) also examines the negative impacts pollution from traffic congestion has on infant health. Exploiting changes in wind direction across highways, Deryugina, Heutel, Miller, Molitor, and Reif (2016) explores the medical costs associated with pollution from traffic.

Several theoretical studies have included HOV lanes to model the effect on congestion. Dahlgren (1998) creates a model to assess the benefits of several different road layout alternatives to combat congestion. A newer theoretical contribution to the study of HOV lanes comes from Konishi and Mun (2010). The authors construct a model to determine when it is socially beneficial to construct an HOV lane. The paper also examines whether converting an HOV to an HOT lane improves road use efficiency. Again, like most other theoretical models in the realm of study, the results depend entirely on the initial parameter values and the welfare functional form.

Duranton and Turner (2011) provide a clear starting point for any empirical research on HOV lanes and their impact on travel times. They evaluate the effect of building additional kilometers of roads on VKT (vehicle kilometers traveled) in the U.S. Interesting and innovative instruments are used to overcome the endogeneity problems associated with road construction including historical maps of highway routes, railway routes, and exploration trails in the United States. Using a comprehensive city-level data set, the authors find that VKT increases proportionally with kilometers constructed (no relief to congestion if additional roads are built). The sources for the extra VKT stem from people migrating to places with more roads, increases in commercial traffic, and current residents just driving more.

With respect to HOV lanes, a new lane may temporarily relieve congestion by drawing vehicles away from the congested general purpose lanes. But, as motorists adjust, those who were constrained by congestion start taking more trips. Additionally, one main assumption in Duranton and Turner (2011) is that all types of interstate road lanes are homogeneous in their purpose for construction; this assumption runs counter to the entire purpose of HOV lanes. Therefore, it is worth exploring to see if these different types of lanes are having similar or different impacts on outcomes such as vehicle miles traveled, congestion, commuting, and pollution than those predicted in Duranton and Turner (2011); that is what the current work directly does with respect to HOV lanes.

Empirical efforts have been made to examine the effect of carpooling and HOV lanes. Examples include: Bento, Hughes, and Kaffine (2013), Hall (2018), Hanna, Kreindler, and Olken (2017), and Hughes and Kaffine (2019). Arguably, the estimates proposed in these studies do not take the endogeneity of HOV lane locations into account: HOV lanes are generally placed in urban areas with high levels of congestion. Therefore, estimating the true treatment effect of HOV lanes with respect to commute times will likely be underestimated by naive OLS specifications.

The paper that is most related to this study is a recent working paper (Shewmake, 2018). This paper theoretically and empirically tests for the impacts of HOV lanes on vehicle miles traveled (VMT). This paper finds the theoretical impacts of HOV lanes on VMT depend upon local conditions, and that empirically, the impacts of HOV lanes are even more ambiguous. Importantly, carpooling is considered endogenous in the model, and the author uses an instrumental variables technique to address the potential bias in the regression estimates. Because of the structure of the Clean Air Act, attainment status may predict where HOV lanes will be built but does not have a direct impact on traffic volume. She uses this instrument (Clean Air Attainment status) to predict the number of HOV lane miles built. However, this instrument is not statistically "strong" on its own. But, when the instrument is interacted with population, Shewmake (2018) finds that HOV lanes are associated with an increase in VMT.

In summary, the negative externalities that stem from commuting have a solid footing in the economics, psychology, and health literatures. However, the economic and behavioral impacts of HOV lanes on commute times has been vastly understudied, especially from an empirical causal inference perspective.[6] This work aims to fill an important gap in the study of transportation and infrastructure investment from a methodological standpoint.

[6] Welfare implications of urban commuting policies have been generally examined (Akbar, Couture, Duranton, Ghani, & Storeygard, 2018; Anderson, 2014; Barrios, Hochberg, & Yi, 2019; Green, Heywood, & Navarro Paniagua, 2020), but HOV lanes less so.

II Institutional Setting and Data

II.a HOV Lanes in California

When examining HOV lanes in the United States, in general, there is some concern about missing data and comparability which could lead to considerable measurement error and biased estimates of the effect of HOV lanes. To the author's knowledge, the most up-to-date across-state compilation of HOV lane location and construction dates was published in 2008 (Chang & Bilotto, 2008). Individually, some states do not have up-to-date transportation and infrastructure information on their respective department of transportation's websites. Therefore, even if data across states' departments of transportation is available, they may or may not be comparable.[7] To avoid these issues, this study focuses on one state that has recently updated HOV lane data: California. California also has the most HOV miles of constructed HOV lanes in the country, making this an ideal place to begin to address if HOV lanes cause increases or decreases in commuting times.

According to the California Department of Transportation, all HOV lanes constructed in California are never converted from existing lanes on highways; due to a mix of state and federal funding laws, all new HOV lanes require new construction.[8] This is unique to California and important to my identification strategy. These lanes are different from HOT (high occupancy toll) or express lanes in that there is no toll or fee associated with using the lane. HOT lanes are not considered in the current analysis.

In addition to the infrastructure institutional set-up discussed above, building roads in California is quite expensive compared to the national average. According to one study, California spent about $420,000 per mile in 2013 compared with the national average spending of about $160,000 per mile in the same year. Building just 10 miles of HOV lanes on I-405 in Los Angeles was estimated to cost over $1 billion.[9] Thus, understanding if the HOV lanes are effective has important policy and budget implications.

[7]This fact is especially true if one wants to analyze HOV lane construction and locations pre-2000.

[8]See Matute and Pincetl (2013) for more details.

[9]Source: http://media.metro.net/projects_studies/pm/images/pm_october_2013_i405_sepulveda_pass_improvements2.pdf

II.a.1 Caltrans Data

The main source of HOV lane data for this paper comes from the California Department of Transportation (Caltrans).[10] Caltrans provides information on the specific location of HOV lanes and other characteristics, including length of the lanes, the location of the lanes, the types of vehicles allowed in the lanes, and other characteristics such as opening and closing times of the lanes. The data from Caltrans were manipulated in QGIS[11] to determine the presence of HOV lanes at the county level. Summary statistics are shown in Panel A of Table 1. Notably, there is considerable variation across the 58 counties of California. Figure 1 maps the locations of all currently constructed HOV lanes in California. Despite there being over 1300 miles of HOV lanes in California, most of these lanes are concentrated in specific urban areas. This apparent selection into certain areas requires addressing. An instrumental variable approach is used to overcome this bias. Additionally, matching methods are used in data pre-processing. Specific details on the instrument, matching methods, and the model specification are discussed in Section 3 of the paper.

[Insert Table 1 Here]

[Insert Figure 1 Here]

[10] California Department of Transportation (2018): http://www.dot.ca.gov/hq/tsip/gis/datalibrary/Metadata/HOV.html

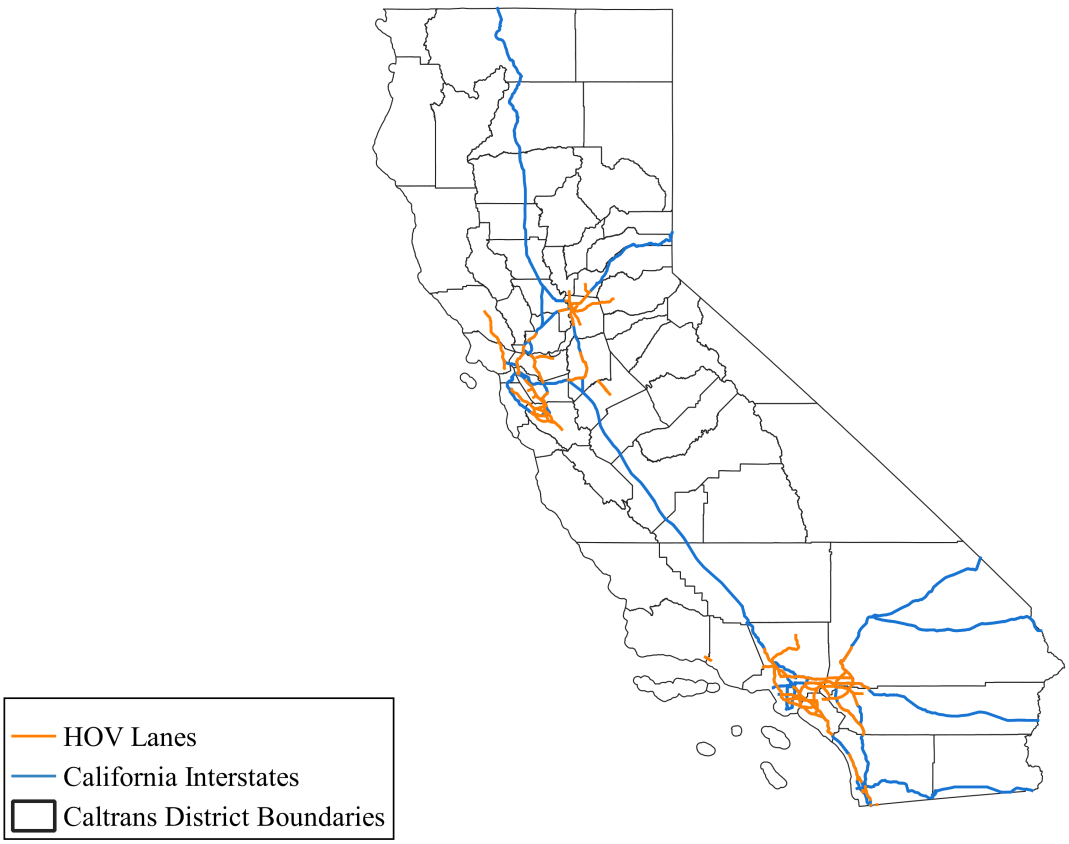
[11] QGIS (Quantum Geographic Information System) is a free, open-source geographic information system software.

Table 1: California HOV Lanes and Commuting

	Mean	S.D.	Min	Max	Total (State)
Panel A: HOV Lanes by County					
Count of HOV Lanes	2.1	5.07	0.00	29.00	124.0
Total HOV miles	23.6	69.20	0.00	438.20	1370.6
N	58 counties				
Panel B: Commuting Characteristics					
Time to Work	27.89	28.66	1.00	600.00	18,939
Short Commute	0.68	0.47	0.00	1.00	18,939
Long Commute	0.33	0.47	0.00	1.00	18,939
Distance to Work	20.87	112.56	0.01	3135.34	18,939
N	18,939 trips				

Notes: Summary statistics for HOV lanes by California county are shown above in Panel A. Data on HOV lanes were sourced from the California Department of Transportation. Summary statistics for California commuting are shown in Panel B. Data is taken from the "Trip" file of the NHTS. Time to work is measured in minutes. Only trips that indicated they were to or from work were examined. Short commute indicates the proportion of California counties that had an average commute time below the state average (27.89 minutes). Long commute indicates the proportion of California counties that had an average commute time above the state average. Distance to work is measured in miles.

Figure 1: California Primary Roads and HOV Lane Locations



Note: Figure displays map of California. Interstates are shown in blue and completed HOV lanes as of 2017 are shown in orange. Although California has the most miles of HOV lanes in the country, most are concentrated in Sacramento, San Francisco, and Los Angeles. HOT (high occupancy toll) lanes, those lanes in which a toll is charged to use the carpool lane, are not included in the analysis.

II.b Commuting in California

Travel data is obtained from the National Household Travel Survey (NHTS) for 2017.[12] The California sub-sample is utilized in this study. 26,112 unique households were surveyed in the sub-sample. The California NHTS data consists of four main files: Household, Person, Trip, and Vehicle. The household file includes information about the households surveyed: home ownership status, family income, how many cars owned, and even the gas price on the day surveyed. The person file includes information about the individuals that make up the households: age, driver

[12] U.S. Department of Transportation: Federal Highway Administration (2018): https://nhts.ornl.gov/

status, education level, relationship status, employment status, how they got to work, and how long it took them to get to work. The trip file describes the times of trips taken by those that were surveyed. Finally, the vehicle file includes detailed information about the make, model, and type of cars owned and driven by those surveyed. These files can be merged and linked with location information that describes where the homes and workplaces of those surveyed are. For this study, all analyses will be conducted at the county level.[13]

Several studies have utilized both the individual state sub-samples, as well as the entire national sample of the National Household Travel Survey. Notably, Plotz, Konduri, and Pendyala (2010) examine the impact of HOV lanes across the entire United States. Conservatively, they attempt to back out the upper and lower bound of HOV lane-induced trip reduction. They find that the impacts of an HOV lane on trip reduction are minimal or modest at best and have little to no impact on operating performance of different lanes. The data have also been used to estimate the effect of different government policies on driving (Spiller, Stephens, Timmins, & Smith, 2012).

Differing from the above studies, the main outcome variable of interest in this study is the amount of time that it takes people to get to or from work (two separate trips) in minutes. This information is taken from the trip file of the NHTS. Analysis was restricted to individual trips whose purpose was to or from work. In this sample, those in the survey that worked outside of the United States were dropped from the analysis, as well as those who worked in another state. Everyone who did not drive to work or worked from home was also dropped from the analysis. Because it is not known with 100% certainty if the survey respondents took an HOV lane to or from work, this specification can only be considered an intent to treat (ITT) analysis. However, if in line with previous empirical studies, the induced demand to drive on a certain road caused by the construction of an additional road lane **impacts all drivers** who drive on that road, not just those who would take an HOV lane. The main mechanisms to be tested are the following: (1) *does the presence of any HOV lanes in your workplace county cause an increase or decrease in your commute time to or from work?* and (2) *does living closer to an HOV lane increase or decrease your commute time to or from work?*

Summary statistics for commuting characteristics are shown in Panel B of Table 1. Similar to HOV lane locations in California, there is considerable variance across the sample of commuters.

[13] Publicly available data from the NHTS includes only a county-level indicator for location of home and work.

Table 2: Urban Size Classifications

Population	Count of Commuters	Percent of Commuters
50,000-199,999	3,175	16.76
200,000-499,999	1,505	7.95
500,000-999,999	1,062	5.61
1 million or more without heavy rail	4,594	24.26
1 million or more with heavy rail	4,767	25.17
Not an urban area	3,836	20.25
Total	18,939	100.00

Notes: Summary statistics for household urban size classification are shown above.

The average time it takes a commuter to get to or from work is about 28 minutes. In general, 70 percent of counties in California have "short commutes" on average (less than the state average of 27.89 minutes) and 30 percent have longer average commutes. The average distance to work is 21 miles. The distance to work is not the straight line distance but the road network distance, in miles, between respondent's home location and work location. This information was sourced using the Google Distance Matrix API. Additionally, information on the dispersion of living locations is provided in the data. As shown in Table 2, the California NHTS surveyed a wide variety of people living in different types of urban areas. Most people in the commuter sub-sample live in urban areas with heavy rail systems and with 1 million or more people. Approximately one fifth of the sample does not live in an urban area.

[Insert Table 2 Here]

II.c Naive Linear Regression

As a first approximation of the effect of HOV lanes on commute times in California, simple naive linear regression models are employed. More specifically, the commute time of driver i in county c in the 2017 California NHTS is estimated in the following way:

$$CommuteTime_{ic} = \beta_1 HOVTreatment_c + \gamma_i + \phi_c + \epsilon_{ic} \tag{1}$$

where HOV treatment is one of the above treatment specifications, β_1 is the variable of interest, γ_i are individual person and trip controls, and ϕ_c are county fixed effects. All standard errors in these naive regressions are clustered at the county level.

Table 3 employs a naive linear regression approach to try to get a baseline estimate of the effect of HOV lanes on commuting times in California. Different treatment definitions are used to try to tease out any heterogeneous impacts. More specifically, five different treatment definitions are used: 1) a 1 or 0 indicator for whether a county has at least one HOV lane passing through it, 2) if a driver's home county centroid is 50 miles or closer to an HOV lane, 3) if a driver's home county centroid is 25 miles or closer to an HOV lane, 4) if a driver's home county centroid is 10 miles or closer to an HOV lane, and 5) if a driver's home county centroid is 5 miles or closer to an HOV lane. Distances between California county centroids and HOV lanes were calculated using QGIS.

In all specifications, controls for the individual driver (age, gender, educational attainment, and occupation type), roadway distance to work, size of the urban area of residence as described in Table 2, and day of travel are employed in the fully specified forms.

Panel A of Table 3 shows the regression results without county fixed effects and Panel B of Table 3 shows the regression results with county fixed effects. In all treatment definitions, HOV lanes and distance to HOV lanes seem to have a positive effect on commute times; in other words, more HOV lanes in the home county of the driver and living relatively close to a HOV lane is related to increased commute times to and from work.

[Insert Table 3 Here]

Adding county fixed effects to the naive regression approach, as shown in Panel B of Table 3, does not change the direction and level of significance; there still appears to be a positive, statistically significant relationship between being treated with HOV lanes and increased commute times to or from work. In naive models, however, this positive effect may be underestimated because HOV lanes are not randomly assigned across the state.

The following section describes the matching procedure implemented as well as the different approaches used to overcome the potential endogeneity problems associated with HOV lane locations and household location decisions.

Table 3: Naive Linear Regression Before Matching: Effect of HOV Lanes on Commute Time

Treatment	(1) Binary	(2) $\leq$ 50 miles	(3) $\leq$ 25 miles	(4) $\leq$ 10 miles	(5) $\leq$ 5 miles
Panel A: No County F.E.					
HOV Lanes	11.04***	10.77***	9.96***	8.31***	7.28***
	(3.93)	(2.25)	(2.27)	(2.46)	(2.25)
	[0.01]	[0.00]	[0.00]	[0.01]	[0.02]
N	18939	18939	18939	18939	18939
Individual Controls	X	X	X	X	X
Distance to Work Control	X	X	X	X	X
Urban Size Controls	X	X	X	X	X
Travel Day Controls	X	X	X	X	X
County Fixed Effects	-	-	-	-	-
R^2	0.056	0.057	0.061	0.054	0.050
Cluster-Robust S.E.	X	X	X	X	X
Panel B: County F.E.					
HOV Lanes	17.77***	32.28***	17.77***	17.77***	17.77***
	(2.42)	(2.24)	(2.42)	(2.42)	(2.42)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
N	18939	18939	18939	18939	18939
Individual Controls	X	X	X	X	X
Distance to Work Control	X	X	X	X	X
Urban Size Controls	X	X	X	X	X
Travel Day Controls	X	X	X	X	X
County Fixed Effects	X	X	X	X	X
R^2	0.11	0.11	0.11	0.11	0.11
Cluster-Robust S.E.	X	X	X	X	X

Notes: * p<0.1, ** p<0.05, *** p<0.01. Cluster-robust standard errors are shown in parentheses and p-statistics are shown in brackets. All models include individual controls (age, sex, education level, occupation type), distance to work controls, urban size controls, and travel day controls. County fixed effects are added in Panel B. Standard errors are clustered at the county level.

III Methods

III.a Coarsened Exact Matching (CEM)

One issue with the naive regression approach is that there is concern that the control and treatment groups across all treatments are not comparable to one another. If these groups are not comparable on observables, then accurate treatment effects cannot be estimated. Table 4 examines the sample means of trip characteristics between treated and non-treated counties in California. The differences between these statistics are shown in Table 4 as well. It is noteworthy that there are significant differences between the treated counties and the control counties in this sample in terms of trip characteristics as well as individual characteristics.

To insure that the treatment and control groups are relatively comparable to accurately estimate the true treatment effect, I employ coarsened exact matching (CEM). Specifically, observations in the treatment group are exactly matched with replacement to observations in the control group: age, gender, educational attainment, occupation type and the trip length measured in roadway miles. CEM matching also helps by not only ensuring individual observation level balance across covariates, but works to ensure global balance across the entire sample (Iacus, King, & Porro, 2011).[14]

Summary statistics for the treated and control groups before matching are shown in Table 4. The means of the control and treatment groups across a select number of covariates are displayed, along with standard errors in parentheses. A t-test was conducted to determine if there are significant differences between the two groups. For the majority of covariates, there are significant differences between the control and treatment groups, lending credence to the motivation for some type of data pre-processing. All additional treatment definitions show a similar pattern; specific estimates for other treatment definitions can be found in the Appendix.

After exact matching with replacement, the means and differences between control and treatment groups are shown in Table 5. There are far fewer differences between the control and treatment groups for the main variables of interest (commute time and distance to work). The remaining differences between the two groups, notably in the industries of employment, are to be expected

[14] See Patrick and Mothorpe (2017) for an empirical application of CEM.

when comparing urban to non-urban areas. Because of this, one can claim that these groups form more comparable comparison groups.

[Insert Table 4 Here]

[Insert Table 5 Here]

Because the matching appears to have corrected much of the covariate imbalance between the control and treatment groups across all treatment definitions, the same linear regression shown in equation 1 was run on the matched samples. The matching had no impact on the level and direction of significance of the coefficients associated with HOV lane treatment. However, the magnitude of the coefficients are smaller. Panel A of Table 6 shows the naive regression after matching without county fixed effects; Panel B of Table 6 shows the same linear regression with county fixed effects.

[Insert Table 6 Here]

In addition to CEM, nearest neighbor matching is imposed on the sample as a robustness test. Using the nearest four neighbors, average treatment effects and average treatment effects on the treated are estimated. Although much smaller than the estimated coefficients from the linear regression approach, the significant, positive relationship between HOV treatment and commute times remains. Treatment effects using this matching approach can be found the Appendix Table A.9.

III.b Instrumental Variable (IV): Democratic Vote Share in 2000

To accurately consider the effects of HOV lanes on commuter behavior, one has to consider the possibly endogenous location choice of HOV lanes, as well as the endogenous choice location of households. Intuitively, one could claim that California is building HOV lanes in more populous, urban areas where traffic congestion is a more of an issue facing commuters. Based on Figure 1, this would seem to be the case. Although California has the most HOV lane miles in the country, most are concentrated in very specific urban areas. A similar conclusion can be drawn from Table 8 below. Unfortunately, up until now, most research conducted to determine the impacts on HOV lanes has not taken this endogeneity of HOV lane location selection into account.

Table 4: Summary Statistics Before Matching

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	22.86	31.37	-20.30***
	(0.30)	(0.280)	[0.00]
Short Commute	0.93	0.50	67.88***
	(0.003)	(0.005)	[0.00]
Long Commute	0.08	0.50	-67.88***
	(0.003)	(0.005)	[0.00]
Distance to work	20.47	21.14	-0.41
	(1.50)	(0.92)	[0.34]
Driver Characteristics			
Male driver	0.48	0.52	-4.66***
	(0.006)	(0.005)	[0.00]
Female driver	0.52	0.48	4.66***
	(0.006)	(0.005)	[0.00]
Less than high school	0.03	0.02	3.84***
	(0.002)	(0.001)	[0.00]
Age	46.24	45.16	5.15***
	(0.17)	(0.13)	[0.00]
Work Characteristics			
Sales	0.23	0.21	2.81***
	(0.005)	(0.004)	[0.003]
Manufacturing	0.14	0.09	9.46***
	(0.004)	(0.003)	[0.00]
Number of trips	7,735	11,204	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table 5: Summary Statistics After Matching

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	22.66	30.73	-18.88***
	(0.28)	(0.32)	[0.00]
Short Commute	0.92	0.52	62.11***
	(0.003)	(0.006)	[0.00]
Long Commute	0.08	0.48	-62.11***
	(0.003)	(0.006)	[0.00]
Distance to work	13.35	16.46	-4.50***
	(0.48)	(0.49)	[0.00]
Driver Characteristics			
Male driver	0.48	0.48	0.00
	(0.006)	(0.006)	[0.50]
Female driver	0.52	0.52	0.00
	(0.005)	(0.005)	[0.50]
Less than high school	0.02	0.02	0.00
	(0.002)	(0.002)	[0.50]
Age	46.01	45.99	0.07
	(0.17)	(0.13)	[0.53]
Work Characteristics			
Sales	0.23	0.23	-1.12
	(0.005)	(0.005)	[0.13]
Manufacturing	0.13	0.10	5.28***
	(0.004)	(0.004)	[0.00]
Number of trips	7,507	7,507	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table 6: Naive Linear Regression After Matching: Effect of HOV Lanes on Commute Time

Treatment	(1) Binary	(2) $\leq$ 50 miles	(3) $\leq$ 25 miles	(4) $\leq$ 10 miles	(5) $\leq$ 5 miles
Panel A: No County F.E.					
HOV Lanes	8.39^{***}	9.68^{***}	8.95^{***}	7.84^{***}	7.33^{***}
	(3.72)	(2.00)	(1.97)	(2.21)	(2.25)
	[0.03]	[0.00]	[0.00]	[0.01]	[0.01]
N	15014	10420	16376	15712	14016
Individual Controls	X	X	X	X	X
Distance to Work Control	X	X	X	X	X
Urban Size Controls	X	X	X	X	X
Travel Day Controls	X	X	X	X	X
County Fixed Effects	-	-	-	-	-
R^2	0.09	0.09	0.09	0.08	0.07
Cluster-Robust S.E.	X	X	X	X	X
Panel B: County F.E.					
HOV Lanes	14.59^{***}	24.21^{***}	15.65^{***}	16.58^{***}	13.62^{***}
	(2.17)	(1.99)	(1.99)	(1.99)	(2.10)
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
N	15014	10420	16376	15712	14016
Individual Controls	X	X	X	X	X
Distance to Work Control	X	X	X	X	X
Urban Size Controls	X	X	X	X	X
Travel Day Controls	X	X	X	X	X
County Fixed Effects	X	X	X	X	X
R^2	0.12	0.14	0.13	0.12	0.11
Cluster-Robust S.E.	X	X	X	X	X

Notes: * p<0.1, ** p<0.05, *** p<0.01. Cluster-robust standard errors are shown in parentheses and p-statistics are shown in brackets. All models include individual controls (age, sex, education level, occupation type), distance to work controls, urban size controls, and travel day controls. County fixed effects are added in Panel B. Standard errors are clustered at the county level.

To overcome this endogeneity problem in HOV lane location selection, an instrumental variables technique will be used. To use HOV lanes to predict commuting times in California, the following two stage estimation is utilized:

$$HOVTreatment_c = \phi_1 DV_c + \gamma_i + \epsilon_{ci} \tag{2}$$

$$CommuteTime_i = \beta_1 \widehat{HOVTreatment}_c + \gamma_i + \upsilon_{ci} \tag{3}$$

where *HOVTreatment* are the different treatment definitions described in Section 2.3, *DV* is share of Democratic votes for president in the 2000 election in county *c*. γ_i includes individual controls (age, sex, educational attainment, and occupation category). Observations (trips) are matched exactly by trip distance in miles and also by individual (trip taker) characteristics.

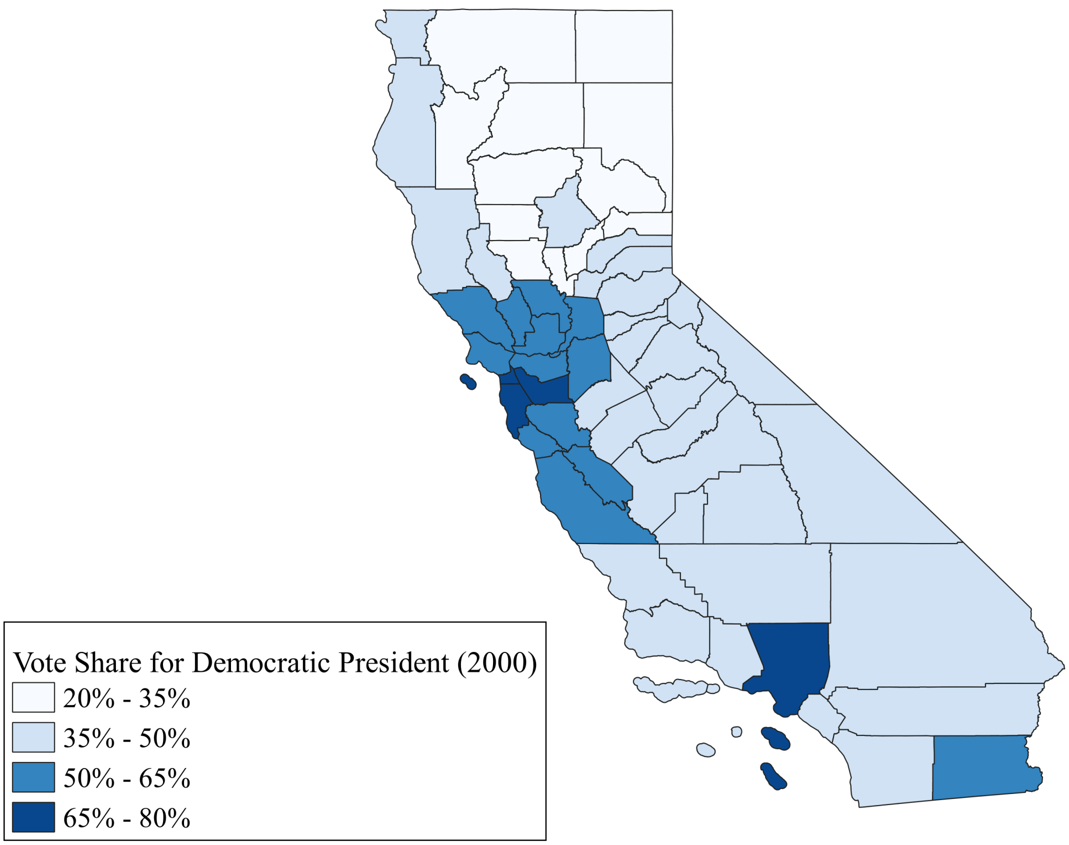
[Insert Figure 2 Here]

To the author's knowledge, this is one of the first studies to use political outcome data to *instrument* for infrastructure construction projects. Many papers cite the link between political outcomes and infrastructure (Brueckner & Selod, 2006; Glaeser & Ponzetto, 2018; Huet-Vaughn, 2019), but using past political outcomes as an instrument for the location of current infrastructure projects is a contribution of the current work. Knowing that one of the major purposes behind the construction of HOV lanes is pollution reduction, counties in California that had a higher vote share for Al Gore in the 2000 presidential election arguably put a higher weight on these environmental issues when compared to counties with a lower vote share.

[Insert Table 7 Here]

To add further weight to the relevance of the instrument, Table 7 summarizes the time trend of HOV lane openings in California. As one can see, the majority of current HOV lanes were opened after 2000. These lanes counted do not even take those lanes currently under construction or approved for construction. Using the vote share in 2000 seems to be a potentially relevant instrument to predict where HOV lanes would later be constructed. Further disaggregation of the

Figure 2: Votes for Al Gore in the 2000 Presidential Election



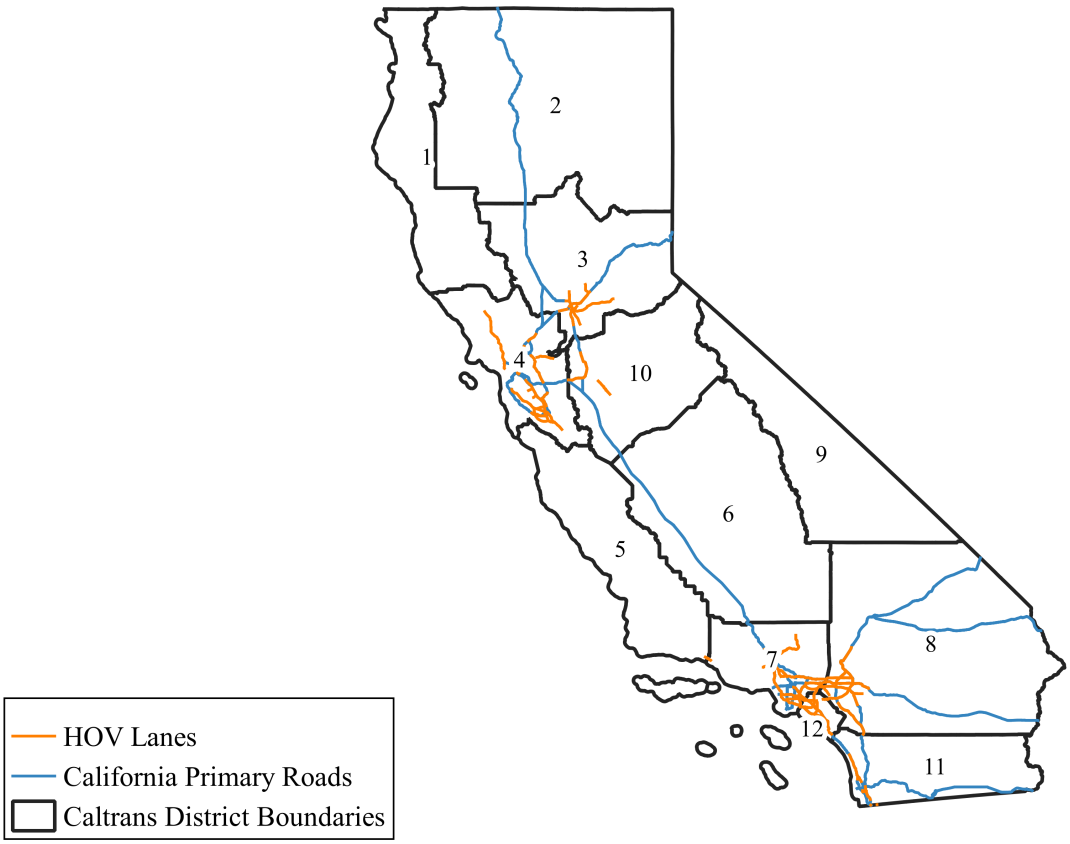
Note: Figure displays heat map of votes for Al Gore in the 2000 presidential election. Higher concentrations of votes may indicate preferences for environmentally friendly pursuits. Comparing with Figure 1, the locations of HOV lanes are highly correlated with larger vote shares for the Democratic party in the 2000 election.

Table 7: Timing of HOV Lane Openings

	Before 2000	In or After 2000	**Total**
# of HOV lanes open (as of 2017)	43	81	124
Under Construction (as of 2017)	-	57	57
Planned Construction	-	11	11

Notes: Table shows the timing of HOV lane construction across the state of California.

Figure 3: HOV Lanes, Primary Roads, and Caltrans Districts



Note: Map shows the divisions of Caltrans districts. Blue lines represent California primary roads, while orange lines represent HOV lanes. Source: `https://dot.ca.gov/caltrans-near-me`

open HOV lane data shows that Caltrans Districts 4 and 7 had the most open HOV lanes before 2000; these same districts also had the most construction of new lanes after 2000. Comparing Table 8 with the voting data displayed in Figure 2, it appears that these districts with the highest propensity for existing and future construction of HOV lanes in and after 2000 correspond to counties with some of the highest Democratic vote shares in the 2000 election.[15]

One could worry that 2000 vote shares for Al Gore is highly correlated with present and potentially future urban density, a factor that would have strong impacts on commute times. If this were the case, the excludability argument for the proposed instrument would not hold. To this point, it is important to note that the voting behaviors in individuals' home counties in 2000 do

[15] A map of the Caltrans districts is shown in Figure 3.

Table 8: Open HOV Lanes by Caltrans District

Caltrans District Major Metro. Area	3 Sacramento	4 San Fran.	7 L.A.	8 San Bern.	11 San Diego	12 Orange County
# of HOV lanes open before 2000	4	10	14	5	4	6
# of HOV lanes open after 2000	8	34	17	12	3	7

Notes: HOV lanes by Caltrans district are shown above. The sample is split before and after 2000 to highlight the persistent nature of HOV lane construction – places that historically had more HOV lanes continued to construct them.

not have an impact on traffic volumes and the time that it takes these individuals to get to work in 2017. But, to control for this potential confounding factor, urban size controls are included in all IV specifications. With this, and other individual and county level controls, conditional exclusion arguments are more grounded.

[Insert Table 8 Here]

III.c IV: 1947 U.S. Highway Plan

For robustness, a second instrument is proposed. Following prominent literature (i.e. Baum-Snow (2007); Duranton and Turner (2011)), the 1947 U.S. Interstate Highway Plan will be used to instrument for current HOV lane locations in California (United States House of Representatives, 1947). Figure 4 displays the 1947 interstate highway plan. This plan to drawn with the purpose of increasing the mobility *between* large cities for trade and national defense purposes. Local driving patterns and commutes were not considered or attempted to be altered with this highway plan.[16]

Specifically, this two-stage estimation technique takes the following form:

$$HOVTreatment_c = \phi_1 1947Plan_c + \gamma_i + \epsilon_{ci} \tag{4}$$

$$CommuteTime_i = \beta_1 HOV\widehat{Treatment}_c + \gamma_i + \upsilon_{ci} \tag{5}$$

[16]The digitized map data used is shown in Figure A.1.

where *HOVTreatment* are the different treatment definitions described in Section 2.3, *1947Plan* is county c's centroid distance to the 1947 highway plan. γ_i includes individual controls (age, sex, educational attainment, and occupation category). Observations (trips) are matched exactly by trip distance in miles and also by individual (trip taker) characteristics.

β_1 is the main coefficient of interest. With conditions of relevance and exclusion, β_1 represents the causal effect of HOV lanes on commuting times. This instrument is relevant to the current analysis because the plan was drawn to efficiently connect urban areas. As shown in Figure 4, the counties in California with more HOV lanes today are also relatively closer to the proposed highways in the 1947 plan. This instrument follows the exclusion restriction because it is unlikely that county distance to nearest 1947 proposed highway impacts an individual's commute time in 2017 except through the plan's influence on future HOV lane location. Because the 1947 plan was drawn without local travel conditions in mind, this adds additional weight to the excludibility of this proposed instrument in predicting commute times. Controls for urban area size, as well as individual and travel controls will be used to further enhance conditional exclusion arguments.

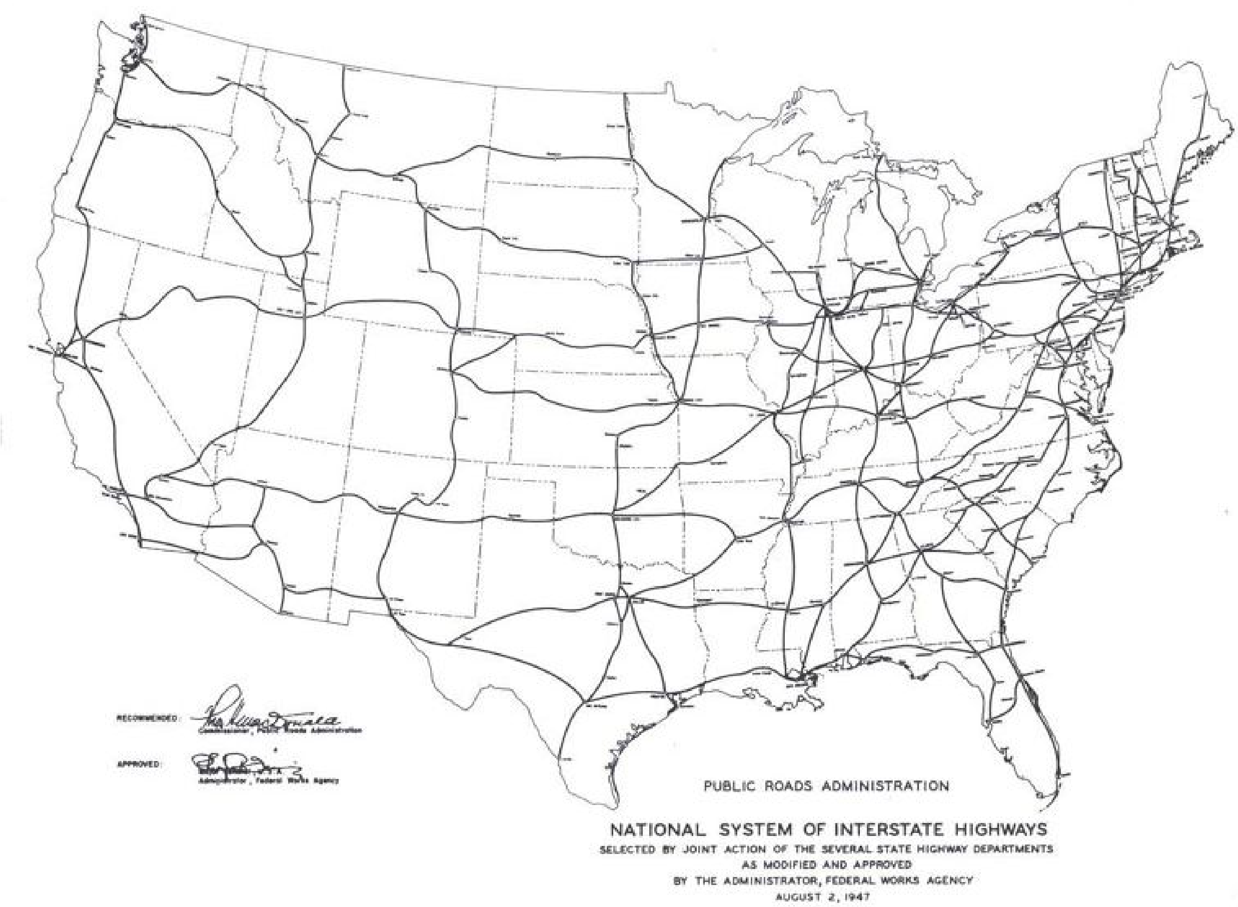
[Insert Figure 4 here.]

IV IV Results

Results for the IV models are presented in Tables 9 and 10. Table 9 reports reduced form, first stage, and second stage results using the 2000 Democratic vote share as an instrument for HOV lane locations. Table 10 reports the reduced form, first stage, and second stage results using the 1947 highway plan as an instrument for HOV lane locations. Robust standard errors are shown in parentheses and first stage F-statistics are also reported. In all model specifications, first-stage F-statistics are well above 10.

When examining the first stage results using the 2000 vote share as an instrument for county distance to HOV lanes, there is a significant and positive coefficient for all treatment definitions. This is shown in column 2 of Table 9. The positive, statistically significant second stage coefficients (column 3 of Table 9) indicate the HOV lanes cause increases in times for people to get to work in California after controlling for the size of the urban area of residence, day of travel, and the

Figure 4: 1947 Interstate Highway Plan



Note: Figure displays the 1947 highway plan drawn by the U.S. House of Representatives. This plan was drawn to increase mobility between U.S. cities for the purposes of domestic trade and national defense. Source: United States House of Representatives (1947).

individuals' personal characteristics (age, sex, occupation) and living distance from work. These results are in line with an induced demand mechanism similar to that found in Duranton and Turner (2011): an increase in the number of road lanes causes an increase in demand to drive on that road, thereby increasing commute times of all who drive on that road.

Noting the coefficient magnitudes, it appears that the induced demand effects of HOV lanes are felt most by those who live relatively close to an HOV lane (5 miles or less). This falls in line with the proposed mechanism as those that live closer to an HOV lane are likely to take a route that has an HOV lane, even if those commuters do not take the HOV lane themselves. Because of the induced demand for the roadway due to the HOV lane, more commuters are likely to take that route, thereby underestimating the amount of commuters who actually use the HOV lane.

Recalling that all new HOV lane construction in California requires the creation of a new lane and not a conversion from an existing lane, the results presented here confirm conclusions posed in Duranton and Turner (2011) that building new road lanes is associated with more vehicle congestion. If some kind of toll was implemented on these lanes, then the desired outcome of reduced travel times to work might be achieved.[17]

[Insert Table 9 Here]

To overcome potential concerns with using vote share as an instrument for HOV lanes, county distance to the 1947 highway plan is used as an instrument for 2017 HOV lane treatments. The first stage results using this instrument, shown in column 2 of Table 10, display a consistently negative and significant relationship. This result would suggest that the larger the county centroid distance to the 1947 plan, the closer that county is to an HOV lane in 2017.

The second stage results are shown in column 3 of Table 10. Similar to Table 9, the second stage results with the 1947 instrument show HOV lanes consistently cause increased commute times, conditional on individual, urban size, and travel day controls. Interestingly, the results found with this instrument do not exhibit the same U-shaped relationship found with the 2000 Democratic vote share instrument – living closer to an HOV lane does not increase commute times relatively

[17] There has been some work regarding the welfare impacts of HOT (high occupancy toll) lanes. The results seem to vary across different areas, and this could be for a number of different reasons beyond the creation of an HOT lane (varying carpooling preferences across places, exogenous factors influencing carpooling, and just the underlying fluctuations in carpooling from day to day and from year to year across places). See Burris, Alemazkoor, Benz, and Wood (2014).

Table 9: 2SLS Estimates With 2000 Democratic Vote Share After Matching: HOV Lanes on Commute Times

	(1) Reduced Form	(2) 1st Stage (ϕ_1)	(3) 2nd Stage (β_1)
Panel A: Any HOV Lane in County			
County Vote Share for Democratic President	49.473***	0.731***	
	(3.679)	(0.040)	
Commute Time to Work			67.651***
			(5.627)
N			15014
Kleibergen-Paap F			320.12
Panel B: $\leq$ 50 miles to nearest HOV Lane			
County Vote Share for Democratic President	46.653***	1.992***	
	(3.926)	(0.040)	
Commute Time to Work			23.419***
			(1.984)
N			10420
Kleibergen-Paap F			2481.92
Panel C: $\leq$ 25 miles to nearest HOV Lane			
County Vote Share for Democratic President	48.149***	2.509***	
	(3.319)	(0.033)	
Commute Time to Work			19.191***
			(1.313)
N			16376
Kleibergen-Paap F			5959.17
Panel D: $\leq$ 10 miles to nearest HOV Lane			
County Vote Share for Democratic President	52.542***	1.740***	
	(3.610)	(0.041)	
Commute Time to Work			30.190***
			(2.107)
N			15712
Kleibergen-Paap F			1790.41
Panel E: $\leq$ 5 miles to nearest HOV Lane			
County Vote Share for Democratic President	53.237***	1.216***	
	(3.615)	(0.043)	
Commute Time to Work			43.784***
			(3.124)
N			14016
Kleibergen-Paap F			800.30

Notes: * p<0.1, ** p<0.05, *** p<0.01. Dependent variable is commute time to work in minutes. Robust standard errors are shown in parentheses. First stage F-statistics are reported, as well as the number of trips included in each treatment definition (N). Instrument for HOV lane treatment is the 2000 vote share for a Democratic president. All models include individual controls (age, sex, education level, occupation type), distance to work controls, urban size controls, and travel day controls.

to living farther away. Still, it is important to note that, no matter the treatment definition or instrument used, the causal effect of HOV lanes is found to be positive and statistically significant. Naive OLS models underestimate the impact of HOV lanes on commute times in California.

[Insert Table 10 Here]

IV.a Limitations and Extensions

One of the major limitations to this study is the lack of detailed commuting data across time. This study only utilizes data from 2017 in California. Additionally, because the commuting data does not ask respondents if they use HOV lanes when they go to or from work, this can still just be seen as an intent to treat analysis. However, if the mechanism of induced demand is at play, the impact of HOV lanes on commute times affects all commuters, not just those who take an HOV lane to or from work.

For further extensions of this paper, more detailed data on HOV lanes could be obtained. Data on HOV lane locations and statuses varies considerably across the country, so expanding this idea beyond California would take a considerable amount of effort. Additionally, the level of analysis in this work may still not be detailed enough to try to accurately capture the effects of HOV lanes. [18]

V Conclusions and Policy Implications

HOV lane construction can be a costly project, but the benefits from this type of project have been arguably understudied, particularly from a causal inference perspective. This paper finds that HOV lanes generally cause an increase in commute times to or from work in California using an instrumental variable approach. To reach these findings, a newly proposed instrument, historic county vote share, as well as a more well-established instrument, the 1947 highway plan, are utilized. The results runs counter to the intended purpose of HOV lanes. This finding follows

[18] Confidential data from the NREL does include information about the drivers' census tract, and even exact latitude and longitude of residence. Re-running the above empirical analysis at the census tract level seems like the next step to try to uncover the true treatment effect of HOV lanes on commute times.

Table 10: 2SLS Estimates With 1947 Highway Plan After Matching: HOV Lanes on Commute Times

	(1) Reduced Form	(2) 1st Stage (ϕ_1)	(3) 2nd Stage (β_1)
Panel A: Any HOV Lane in County			
Distance to 1947 Plan	-0.071***	-0.004***	
	(0.009)	(0.000)	
Commute Time to Work			16.675***
			(2.146)
N			15014
Kleibergen-Paap F			1532.11
Panel B: $\leq$ 50 miles to nearest HOV Lane			
Distance to 1947 Plan	-0.055***	-0.002***	
	(0.010)	(0.000)	
Commute Time to Work			25.590***
			(4.623)
N			10420
Kleibergen-Paap F			215.941
Panel C: $\leq$ 25 miles to nearest HOV Lane			
Distance to 1947 Plan	-0.073***	-0.004***	
	(0.009)	(0.000)	
Commute Time to Work			14.719***
			(1.881)
N			16376
Kleibergen-Paap F			1734.42
Panel D: $\leq$ 10 miles to nearest HOV Lane			
Distance to 1947 Plan	-0.080***	-0.007***	
	(0.010)	(0.000)	
Commute Time to Work			12.154***
			(1.536)
N			15712
Kleibergen-Paap F			2872.85
Panel E: $\leq$ 5 miles to nearest HOV Lane			
Distance to 1947 Plan	-0.079***	-0.007***	
	(0.012)	(0.000)	
Commute Time to Work			11.024***
			(1.628)
N			14016
Kleibergen-Paap F			2816.89

Notes: * p<0.1, ** p<0.05, *** p<0.01. Dependent variable is commute time to work in minutes. Robust standard errors are shown in parentheses. First stage F-statistics are reported, as well as the number of trips included in each treatment definition (N). Instrument for HOV lane treatment is the county centroid distance to nearest segment of the 1947 highway plan. All models include individual controls (age, sex, education level, occupation type), distance to work controls, urban size controls, and travel day controls.

previous literature discussing the impact of additional road lane construction (Duranton & Turner, 2011). The induced demand from an additional road lane, regardless of its intended purpose, seems to directly influence the commute times of *all* who drive on that road. If these lanes are not reducing commute times, as is their intention, the potential negative consequences associated with increased commutes and congestion are numerous.[19]

The policy implications of these findings are particularly important considering that all new HOV lanes in California are essentially new roads (never converted from existing roads). Not only is road construction expensive, it is particularly expensive in California due to high land and labor costs. To recover some lost revenue from constructing these lanes, the California Department of Transportation could convert them into HOT or express lanes. If places want to keep them free, counties could promote the use of ride sharing apps and make carpooling easier for those going to or coming home from work.

[19]Most obvious are the increase in aggressive and stressful emotions of drivers and additional health risks associated with pollution from car emissions. See Currie and Walker (2011) and Hennessy and Wiesenthal (1999) for two of numerous examples of consequences of increased traffic and commute times.

References

Akbar, P. A., Couture, V., Duranton, G., Ghani, E., & Storeygard, A. (2018). *Mobility and congestion in urban India*. The World Bank.

4

Albouy, D., & Lue, B. (2015). Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life. *Journal of Urban Economics*, *89*, 74–92.

2

Anderson, M. L. (2014). Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion. *American Economic Review*, *104*(9).

4

Barrios, J. M., Hochberg, Y. V., & Yi, H. (2019). The cost of convenience: Ridehailing and traffic fatalities. *Available at SSRN 3361227*.

4

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics*, *122*(2), 775-805.

2, 21

Bento, A. M., Hughes, J. E., & Kaffine, D. (2013). Carpooling and driver responses to fuel price changes: Evidence from traffic flows in Los Angeles. *Journal of Urban Economics*, *77*, 41–56.

4

Brueckner, J. K., & Selod, H. (2006). The political economy of urban transport-system choice. *Journal of Public Economics*, *90*(6-7), 983–1005.

18

Burris, M., Alemazkoor, N., Benz, R., & Wood, N. (2014). The impacts of HOT lanes on carpools. *Research in Transportation Economics*, *44*, 43-51.

24

California Department of Transportation. (2018). *High occupancy vehicle lanes.* Retrieved 2018-11-15, from http://www.dot.ca.gov/hq/tsip/gis/datalibrary/Metadata/HOV.html

6

Chang, J. W. A. S., M., & Bilotto, C. (2008). A compendium of existing of HOV lane facilities in the United States. *Final report to the US DOT FHWA*.

5

Currie, J., & Walker, R. (2011, January). Traffic congestion and infant health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, *3*(1), 65-90.

2, 28

Dahlgren, J. (1998). High occupancy vehicle lanes: Not always more effective than general purpose lanes. *Transportation Research, Part A: Policy and Practice*, *32*(2), 99-114.

3

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2016). *The mortality and medical costs of air pollution: Evidence from changes in wind direction* (Tech. Rep.). National Bureau of Economic Research.

3

Duranton, G., & Turner, M. (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review*, *101*(6), 2616-2652.

1, 2, 3, 21, 24, 28

Eliasson, J. (2009). A cost–benefit analysis of the Stockholm congestion charging system. *Transportation Research Part A: Policy and Practice*, *43*(4), 468–480.

1

Glaeser, E. L., & Ponzetto, G. A. (2018). The political economy of transportation investment. *Economics of Transportation*, *13*, 4–26.

18

Green, C. P., Heywood, J. S., & Navarro Paniagua, M. (2020). Did the London congestion charge reduce pollution? *Regional Science and Urban Economics*, *84*, 103573.

4

Hall, J. D. (2018). Pareto improvements from Lexus Lanes: The effects of pricing a portion of the lanes on congested highways. *Journal of Public Economics*, *158*, 113 - 125.

4

Hanna, R., Kreindler, G., & Olken, B. A. (2017). Citywide effects of high-occupancy vehicle restrictions: Evidence from "three-in-one" in Jakarta. *Science*, *357*(6346), 89–93.

4

Hennessy, D. A., & Wiesenthal, D. L. (1999). Traffic congestion, driver stress, and driver aggression. *Aggressive Behavior*, *25*(6), 409-423.

2, 28

Huet-Vaughn, E. (2019). Stimulating the vote: ARRA road spending and vote share. *American Economic Journal: Economic Policy*, *11*(1), 292–316.

18

Hughes, J. E., & Kaffine, D. (2019). When should drivers be encouraged to carpool in HOV lanes? *Economic Inquiry*, *57*(1), 667-684.

4

Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, *106*(493), 345–361.

13

Knittel, C. R., Miller, D. L., & Sanders, N. J. (2016). Caution, drivers! Children present: Traffic, pollution, and infant health. *Review of Economics and Statistics*, *98*(2), 350–366.

3

Konishi, H., & Mun, S. (2010). Carpooling and congestion pricing: HOV and HOT lanes. *Regional Science and Urban Economics*, *40*, 173-186.

3

Leape, J. (2006). The London congestion charge. *Journal of Economic Perspectives*, *20*(4), 157-176.

1

Matute, J., & Pincetl, S. (2013). High-occupancy vehicle expansion through lane conversion rather than new construction. *Petroleum Policy Brief Series*.

5

Patrick, C., & Mothorpe, C. (2017). Demand for new cities: Property value capitalization of municipal incorporation. *Regional Science and Urban Economics*, *67*, 78-89.

13

Plotz, J., Konduri, K., & Pendyala, R. (2010). To what extent can high-occupancy vehicle lanes reduce vehicle trips and congestion? Exploratory analysis using national statistics. *Transportation Research Record*, *2178.1*, 170-176.

9

Santos, G. (2005). Urban congestion charging: A comparison between London and Singapore. *Transport Reviews*, *25*(5), 511–534.

1

Shewmake, S. (2018). The impact of high occupancy vehicle lanes on vehicle miles traveled. *Working Paper*.

4

Spiller, E., Stephens, H., Timmins, C. D., & Smith, A. (2012). Does the substitutability of public transit affect commuters' response to gasoline price changes? *Resources for the Future Discussion Paper No.12-29*.

9

United States House of Representatives. (1947). *A report on the National Interregional Highway Committee, outlining and recommending a national system of interregional highways* (Tech. Rep.). Washington, DC: US Government Printing Office.

21, 23

U.S. Department of Transportation: Federal Highway Administration. (2018). *National household travel survey.* Retrieved 2018-10-10, from https://nhts.ornl.gov/

8

A Appendix

Table A.1: Trip and Driver Characteristics Before Matching: 50 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	21.06	30.53	-20.59***
	(0.30)	(0.260)	[0.00]
Short Commute	0.999	0.55	65.38***
	(0.004)	(0.004)	[0.00]
Long Commute	0.001	0.45	-65.38***
	(0.004)	(0.004)	[0.00]
Distance to work	22.12	20.39	-0.95
	(2.00)	(0.83)	[0.17]
Driver Characteristics			
Male driver	0.48	0.51	-3.57***
	(0.006)	(0.004)	[0.00]
Female driver	0.52	0.49	3.57***
	(0.006)	(0.004)	[0.00]
Less than high school	0.03	0.02	3.33***
	(0.002)	(0.001)	[0.00]
Age	46.51	45.25	5.48***
	(0.20)	(0.12)	[0.00]
Work Characteristics			
Sales	0.25	0.21	6.23***
	(0.006)	(0.003)	[0.00]
Manufacturing	0.14	0.09	9.46***
	(0.004)	(0.003)	[0.00]
Number of trips	5,268	13,671	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.2: Trip and Driver Characteristics After Matching: 50 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	21.04	29.72	-17.55***
	(0.30)	(0.40)	[0.00]
Short Commute	0.999	0.57	62.81***
	(0.004)	(0.007)	[0.00]
Long Commute	0.001	0.43	-62.81***
	(0.004)	(0.007)	[0.00]
Distance to work	14.34	17.32	-2.18***
	(0.96)	(0.97)	[0.01]
Driver Characteristics			
Male driver	0.48	0.48	0.00
	(0.007)	(0.007)	[0.50]
Female driver	0.52	0.52	0.00
	(0.007)	(0.007)	[0.50]
Less than high school	0.03	0.03	0.00
	(0.002)	(0.002)	[0.50]
Age	46.46	46.45	0.02
	(0.20)	(0.20)	[0.51]
Work Characteristics			
Sales	0.25	0.25	0.57
	(0.006)	(0.006)	[0.71]
Manufacturing	0.14	0.12	4.78***
	(0.005)	(0.004)	[0.00]
Number of trips	5,210	5,210	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.3: Trip and Driver Characteristics Before Matching: 25 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	22.65	32.78	-24.70***
	(0.32)	(0.25)	[0.00]
Short Commute	0.99	0.38	120.02***
	(0.001)	(0.005)	[0.00]
Long Commute	0.001	0.62	-120.00***
	(0.001)	(0.004)	[0.00]
Distance to work	20.38	21.32	-0.57
	(1.36)	(0.95)	[0.28]
Driver Characteristics			
Male driver	0.49	0.51	-2.43***
	(0.01)	(0.01)	[0.01]
Female driver	0.51	0.49	2.43***
	(0.01)	(0.01)	[0.01]
Less than high school	0.03	0.02	2.13***
	(0.002)	(0.002)	[0.02]
Age	45.82	45.40	2.03***
	(0.15)	(0.14)	[0.02]
Work Characteristics			
Sales	0.24	0.20	6.98***
	(0.004)	(0.004)	[0.00]
Manufacturing	0.13	0.09	7.46***
	(0.003)	(0.003)	[0.00]
Number of trips	9,128	9,811	

Notes: * p<0.1, ** p<0.05, *** p<0.01. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.4: Trip and Driver Characteristics After Matching: 25 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	22.63	32.43	-23.12***
	(0.26)	(0.34)	[0.00]
Short Commute	0.99	0.39	110.36***
	(0.001)	(0.005)	[0.00]
Long Commute	0.006	0.61	-110.00***
	(0.001)	(0.054)	[0.00]
Distance to work	13.88	17.81	-4.61
	(0.59)	(0.61)	[0.00]
Driver Characteristics			
Male driver	0.49	0.49	0.00
	(0.01)	(0.01)	[0.50]
Female driver	0.51	0.51	0.00
	(0.01)	(0.01)	[0.50]
Less than high school	0.03	0.03	0.00
	(0.002)	(0.002)	[0.50]
Age	45.68	45.71	-0.14
	(0.16)	(0.16)	[0.45]
Work Characteristics			
Sales	0.24	0.20	2.29***
	(0.005)	(0.005)	[0.00]
Manufacturing	0.12	0.10	2.80***
	(0.004)	(0.003)	[0.00]
Number of trips	8,188	8,188	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.5: Trip and Driver Characteristics Before Matching: 10 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	24.04	33.09	-21.75***
	(0.25)	(0.35)	[0.00]
Short Commute	0.92	0.35	104.23***
	(0.003)	(0.005)	[0.00]
Long Commute	0.08	0.65	-100.00***
	(0.003)	(0.005)	[0.00]
Distance to work	20.10	21.90	-1.09
	(1.18)	(1.08)	[0.14]
Driver Characteristics			
Male driver	0.49	0.51	-2.55***
	(0.01)	(0.01)	[0.01]
Female driver	0.51	0.49	2.55***
	(0.01)	(0.01)	[0.01]
Less than high school	0.03	0.02	2.84***
	(0.002)	(0.002)	[0.02]
Age	45.77	45.36	1.94***
	(0.14)	(0.15)	[0.02]
Work Characteristics			
Sales	0.23	0.21	4.95***
	(0.004)	(0.004)	[0.00]
Manufacturing	0.12	0.09	6.29***
	(0.003)	(0.003)	[0.00]
Number of trips	10,866	8,073	

Notes: * p<0.1, ** p<0.05, *** p<0.01. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.6: Trip and Driver Characteristics After Matching: 10 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	24.22	32.74	-19.38***
	(0.28)	(0.34)	[0.00]
Short Commute	0.92	0.35	90.92***
	(0.003)	(0.005)	[0.00]
Long Commute	0.08	0.65	-90.92***
	(0.003)	(0.005)	[0.00]
Distance to work	13.94	17.67	-4.90***
	(0.53)	(0.55)	[0.00]
Driver Characteristics			
Male driver	0.51	0.51	0.00
	(0.01)	(0.01)	[0.50]
Female driver	0.49	0.49	0.00
	(0.01)	(0.01)	[0.50]
Age	45.27	45.29	-0.09
	(0.16)	(0.16)	[0.46]
Less than high school	0.02	0.02	0.00
	(0.002)	(0.002)	[0.50]
Work Characteristics			
Sales	0.21	0.20	1.00
	(0.003)	(0.003)	[0.16]
Manufacturing	0.11	0.09	2.57***
	(0.003)	(0.003)	[0.01]
Number of trips	7,856	7,856	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.7: Trip and Driver Characteristics Before Matching: 5 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	24.79	33.14	-19.58***
	(0.24)	(0.38)	[0.00]
Short Commute	0.86	0.37	79.78***
	(0.003)	(0.006)	[0.00]
Long Commute	0.14	0.63	-79.78***
	(0.003)	(0.006)	[0.00]
Distance to work	20.96	20.71	0.14
	(1.13)	(1.08)	[0.44]
Driver Characteristics			
Male driver	0.49	0.51	-2.67***
	(0.01)	(0.01)	[0.03]
Female driver	0.51	0.48	2.67***
	(0.01)	(0.01)	[0.00]
Age	45.84	45.19	3.04***
	(0.13)	(0.16)	[0.00]
Less than high school	0.03	0.02	2.88***
	(0.002)	(0.002)	[0.00]
Work Characteristics			
Sales	0.23	0.20	5.00***
	(0.004)	(0.005)	[0.00]
Manufacturing	0.12	0.09	5.41***
	(0.002)	(0.003)	[0.00]
Number of trips	11,889	7,050	

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.8: Trip and Driver Characteristics After Matching: 5 miles or less

	Control County	Treated County	Difference
Trip Characteristics			
Time to Work	25.15	32.92	-16.47***
	(0.30)	(0.36)	[0.00]
Short Commute	0.85	0.37	66.99***
	(0.004)	(0.006)	[0.00]
Long Commute	0.14	0.63	-66.99***
	(0.004)	(0.006)	[0.00]
Distance to work	14.82	17.45	-3.14***
	(0.58)	(0.61)	[0.00]
Driver Characteristics			
Male driver	0.51	0.51	0.00
	(0.01)	(0.01)	[0.50]
Female driver	0.49	0.49	0.00
	(0.01)	(0.01)	[0.50]
Age	45.16	45.16	-0.03
	(0.16)	(0.16)	[0.48]
Less than high school	0.02	0.02	0.00
	(0.002)	(0.002)	[0.50]
Work Characteristics			
Sales	0.21	0.20	1.50*
	(0.005)	(0.005)	[0.06]
Manufacturing	0.10	0.09	1.57*
	(0.004)	(0.003)	[0.06]
Number of trips	7,008	7,008	

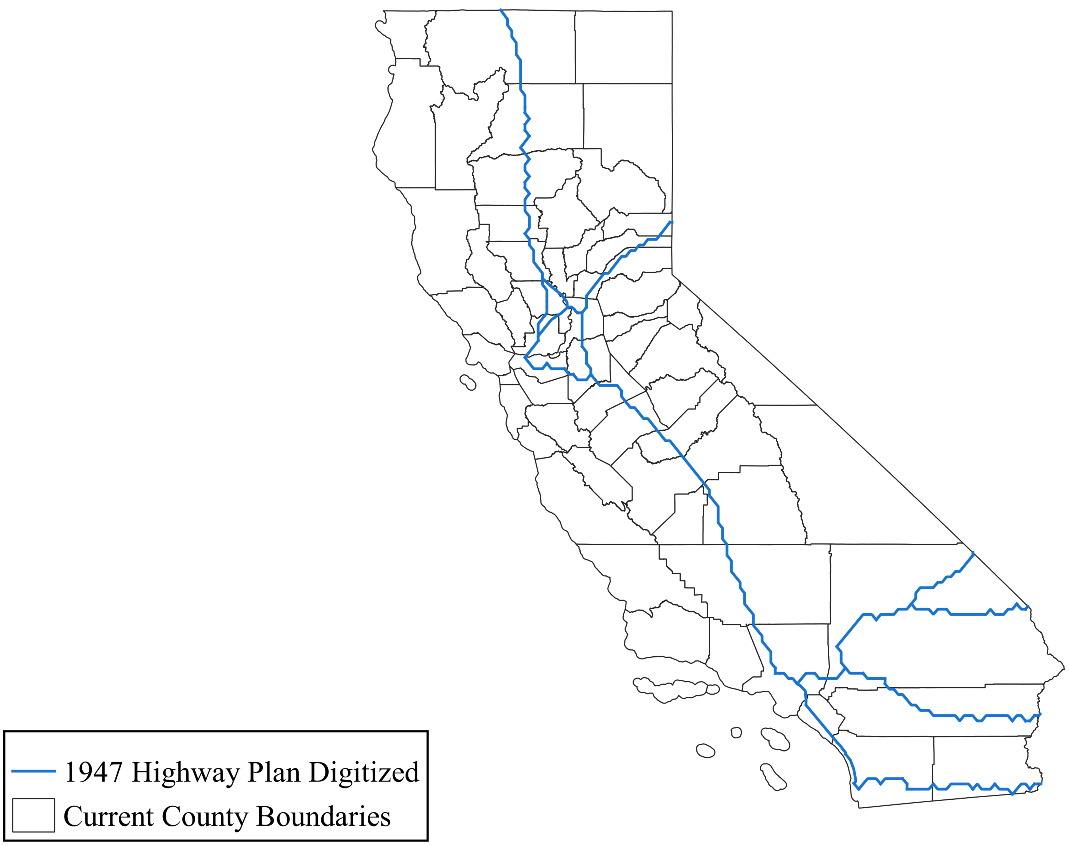
Notes: * p<0.1, ** p<0.05, *** p<0.01. Means for control and treated counties are shown above. T-tests were used to test for the difference in means. Standard errors are shown in parentheses and p-values are shown in brackets.

Table A.9: Nearest Neighbor Matching Analysis

	Average Treatment Effect	Average Treatment Effect on the Treated
Binary Treatment	5.68***	6.85***
	(0.34)	(0.36)
$\leq$ 50 miles	7.91***	8.83***
	(0.31)	(0.31)
$\leq$ 25 miles	6.84***	8.28***
	(0.34)	(0.34)
$\leq$ 10 miles	5.19***	6.81***
	(0.34)	(0.38)
$\leq$ 5 miles	5.01***	6.56***
	(0.36)	(0.39)

Notes: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Nearest neighbor average treatment effects and average treatment effects on the treated are displayed for all HOV treatment definitions' impacts on commute time. The four nearest neighbors were used to calculate these effects. Robust standard errors are shown in parentheses.

Figure A.1: 1947 Interstate Highway Plan Digitized



Note: Figure displays the 1947 highway plan drawn by the U.S. House of Representatives (Figure 4) in its digitized form. Figure only displays the plan's lines drawn for California. Figure created using QGIS.